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Weather, the Forgotten Factor in Business Cycle Analyses

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Roland Döhrn and Philipp an den Meulen[1]

Weather, the Forgotten Factor in Business Cycle Analyses

Abstract

In periods of unusual weather, forecasters face a problem of interpreting economic data: Which part goes back to the underlying economic trend and which part arises from a special weather effect? In this paper, we discuss ways to disentangle weather-related from business cycle-related influences on economic indicators. We find a significant influence of weather variables at least on a number of monthly indicators. Controlling for weather effects within these indicators should thus create opportunities to increase the accuracy of indicator-based forecasts. Focusing on quarterly GDP growth in Germany, we find that the accuracy of the RWI short term forecasting model improves but advances are small and not significant.

JEL Classification: C53, E37

Keywords: Weather; short term forecasting; bridge equations; forecast accuracy

January 2015

1 Both RWI. – This paper benefited from valuable comments by the participants of the 9th Workshop „Makroökonomik und Konjunktur" on November 20th and 21st 2014 in Dresden, in particular from Kai Hielscher. *– All correspondence to: Roland Döhrn, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: doehrn@rwi-essen.de*

1. Introduction

In the first months of 2014, people have witnessed extreme weather conditions in North America as well as in Central Europe. While in the US, the winter was extremely cold and icy hampering economic activity to a substantial degree, in Germany, the winter was unusually mild. There, activity in the construction sector was “biased” upwards since it was not impeded by unfavorable weather conditions as it is usually the case during winters.

In terms of forecasting, periods of extraordinary weather conditions are difficult to deal with. Döhrn (2014a) has shown that forecasts for Germany published in spring tend to be over-optimistic after mild winters and tend to be too pessimistic after cold ones. This suggests that it may be difficult to separate the underlying tendency in the business cycle from the special influence of weather. Seasonal adjustment methods seem to aggravate this problem, since they are based on pure time series models and do not incorporate weather information explicitly, although this would be possible (Bundesbank 2012).

In principle it is widely acknowledged that weather influences the economy. Dell et al. (2013) have collected a plethora of studies dealing with various channels through which economic activity may be affected by weather and climate conditions. For obvious reasons, agriculture is one of these channels and the energy sector is another one. Furthermore, Dell et al. (2013) cite quite a number of studies showing that high temperature has a negative impact on productivity and thus on output, which may explain differences in the economic performance between countries and regions. Another strand of the literature deals with the consequences of natural disasters. Among others, Loayza et al. (2009) analyze the impact of droughts, floods, earthquakes and storms on GDP growth. They find a negative impact of droughts in particular in developing countries, whereas floods even increase GDP growth when a five years period is taken into consideration. Fomby et al. (2009), using the same dataset to estimate the effects on growth annually, find that the negative impact of droughts can be felt over a longer period. The positive impact of floods can only be found after moderate ones, and they materialize about two years after the event.

However, the studies mentioned hitherto primarily focus on medium term effects. The shortest period of time they consider is one year. The consequences of weather events in a shorter run, in particular their impact on monthly economic indicators, has so far received much less attention. This is quite surprising given the importance of such effects for business cycle analyses. Here, again, some more systematic studies have been conducted in the aftermath of economic disasters (e.g. Berlemann, Vogt 2007).[4] While the importance of weather effects on short-term economic activity is often acknowledged by forecasters[5], to the best of our knowledge a systematic analysis has not been conducted yet.

The present paper tries to fill this gap. Here, weather will be understood as shorter-term variations of climatic variables, to distinguish it from climate, which summarizes trends in such variable over longer periods (Dell et al. 2013: 3). The analyses will be restricted to Germany. Furthermore, they will concentrate on the impact of temperature, more specifically of low temperature.[6] Firstly, this seems to be the factor which is the most relevant in a country located in a temperate climate zone. Secondly, the influence of other weather events such as strong rain causing floods will be felt only in some regions but not in the economy as a whole.

One might argue that variations of the temperature over the year will be covered by seasonal adjustment. This is partly true. Seasonal adjustment techniques are able to control for the fact that, e.g. in February, the weather is typically colder than in August. However, since seasonal adjustment techniques are based on time series models which do not take into account the causes of seasonal variations, they can extract only the effect of an “average winter” or an “average summer”

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[4] Narron et al (2014) describe one of the rare cases in which a weather event caused an economic crisis. In 1799, Hamburg experienced a boom as it benefited from the blockade of British ports during the Napoleon wars. A strong winter, which made the Hamburg port unreachable for ships, then caused a recession.

[5] See e.g. Döhrn et al. (2013: 50), Fichtner et al. (2014: 211-213, GD (2014: 39, 42)

[6] In the Bundesbank (2014) study for the U.S. also cooling days are considered.

from the data. When time series techniques were introduced in the 1930s, there was a discussion to conduct also a temperature adjustment (Bell and Hilmer 1987: 301). However, this aspect has not become a standard tool thereafter, although it is possible in a technical sense, as Bundesbank (2014) and Ouwehand, van Ruth (2014) have demonstrated in a CENSUS X12 context. The main argument for weather adjustment not having become a standard tool is that it might be difficult to measure weather appropriately and above all in a comparable way for different countries and different kinds of economic activity.[7] Therefore, a first section of this paper discusses various approaches to condense weather information into a single variable that can be included into economic analyses.

In a second part, an outline of the research strategy will be given. In principle, one can think about two ways to include weather variables into economic analyses. A first way would be to conduct a weather adjustment of time series in addition to a seasonal adjustment. The studies of Bundesbank (2014) and Ouwehand, van Ruth (2014) give examples of such an adjustment. However, for forecasters it would be difficult to follow this approach, since there are no "official" weather adjusted figures. This may lead to a situation in which different forecasters use different methods and results would not be comparable. Therefore, we follow an approach in which we integrate weather variables into the models producing short term forecasts of GDP growth for the current quarter and one quarter ahead.

It is obvious that weather effects can be found primarily in the construction sector. In a third part we analyze which other economic indicators exhibit a weather effect, too. This analysis is based on a balanced and broad-based set of 49 indicators that enter the RWI short term forecasting model as stationary variables.[8] In what follows this model will be used to conduct a forecast analysis.

In the fourth part, we present the results of the forecast analysis and investigate to what extent accuracy increases if the model is augmented

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[7] Ouwehand and van Ruth (2014), e.g, find in their study for the Netherlands significant results for four different weather variables.

[8] See Table 5 for the set of indicators.

by weather. We find that some indicators are affected by unusual weather conditions, albeit the number is not very large. Hence, accounting for weather effects within indicators, forecast errors of the RWI model can be reduced slightly, but the improvement is not significant. Despite this finding, in the final part we conclude that disentangling weather-related from business cycle-related effects may be a promising approach to improve forecast accuracy.

2. How to measure weather conditions

Measuring the impact of weather conditions on the economy is far from being trivial. It is true, that various aspects of weather such as temperature or the amount of rain are well measurable and well documented. However, the relation to economic activity can be expected not to be linear. A shift of temperature from 20° C to 10° C can be expected to be little relevant or even irrelevant for economic activity whereas a shift of the same magnitude from 0° C to -10° C might interrupt production in the construction sector. And if low temperature is associated with ice or snow, the economic consequences will be different once more, since also the transportation sector will be directly affected. Furthermore, the duration of extreme weather conditions may play a role. If the occurrence of ice and snow is not covered by a weather indicator, but only temperature, such indicator may be misleading in measuring economic disturbances caused by the weather. Furthermore, some days of ice and snow distributed randomly over the winter months may be less harmful for the economy than a longer lasting period of extremely low temperature which may cut off industries from their supplies.

Ouwehand and van Ruth (2014) propose various weather indicators which are generated by transforming daily weather observations. One is the so-called “degree days”, defined as the sum of the deviation of the daily average temperature from 18°C, taking into account only days with temperature below 18°C, which also is used by Deutsche Bundesbank (2014).

As a first weather variable in this study, we use a figure which is calculated similarly as the one outlined above but is different in two respects. Firstly, we set the threshold for classifying a month as "cold" at a lower level, since in the end temperatures above 0°C, even if they require heating, should show no negative impact on economic activity. Secondly, we use monthly data, and therefore the threshold will not be set at 0°C, since it can be expected that in a month with an average temperature of, e.g., 5°C at least some days with a maximum temperature below 0°C can be expected. In what follows, we set the threshold at 7.5°C which admittedly is arbitrary but seems to be a reasonable setting in view of the results below. Thus, our variable "temperature deficit" is defined as the difference between the monthly average temperature and 7.5°C. If the monthly temperature is below the threshold it will be set equal to zero, while it is set equal to one if the opposite is true. This figure is calculated in a first step based on data provided by 48 weather stations.[9] In a second step, average temperature figures for the German *Länder* are calculated, to take into account that only one observation exists for *Länder* covering a small area whereas there are several observations for larger ones. To end up with a national figure, in a third step, a weighted average of the *Länder* figures is calculated using the population as weights.[10]

As second weather variable, which also has been proposed by Ouwehand and van Ruth (2014), we will use the number of frost days, i.e. of days with a minimum air temperature below 0°C. Again, data from 48 weather stations are taken into consideration. We aggregate them in the same way as described above to get a national figure. In some studies also the number of ice days is employed, which are defined as days with a maximum air temperature below 0°C. Bundesbank (2014) as well as Hielscher and Enkelmann (2014) find the number of ice days to be the most powerful weather indicator for the construction sector. For data reasons we left this variable out of consideration here. However, by reducing the threshold of the temperature deficit variable we can generate a variable which indicates

[9] The weather stations have been selected with respect to the economic importance of the region they are located. Weather stations with extreme climatic conditions, e.g. such located on high mountains, have not been considered because of their small relevance for economic activity.

[10] We also used *Länder* GDP as weights, which did not improve our results.

the number of extremely cold days. In the context of our study, temperature deficit with a lower threshold of 2.5°C did not lead to lower forecast errors.

A third weather variable does not require any aggregation since we take it from a nationwide survey, the ifo business survey. In its survey, the ifo institute asks companies from the construction sector whether their production activities are hindered by bad weather conditions. The share of companies giving an affirmative answer is used as an indicator how strong economic activity is impeded by bad weather. Using this variable, we broaden our view, taking into account unfavorable weather conditions of any kind.

Since it can be assumed that the typical influence of weather during the year is already covered by seasonal adjustment, the three indicators will be normalized to giving the deviations from the respective long term monthly averages. For Germany, these are shown in chart 1 for the years after the re-unification. It can be seen that the temperature deficit and the frost days variable are highly correlated (r=0,935), whereas the correlation with the ifo survey is lower (frost days: r = 0,500; temperature deficit: r=0,544).[11] Furthermore, the volatility of the variables seems to have been risen somewhat over time.

3. Short term forecasting with weather information

In order to include weather information into short term forecasting models of GDP, we adhere to a widely spread approach in this context, which is estimating bridge equations. The general form of a representative bridge equation looks like:

$$Y_t = Y_t(I_{1,t}, I_{1,t-1}, I_{1,t-2},\ldots, I_{2,t}, I_{2,t-1}, I_{2,t-2},\ldots, \ldots, I_{n,t}, I_{n,t-1}, I_{n,t-2}, \ldots, Y_{1,t-1}, Y_{1,t-2},\ldots), \quad (1)$$

where n is some subset of the whole set of indicators N. Hence, the bridge equation is to regress GDP (Y_t) on past and present values of a subset of indicators (I_1, I_2, …, I_n) and on past values of GDP.

[11] In part this may be due to the fact that the survey also indicates impediments due to weather over summer which may reflect heat or heavy rain.

There is a huge amount of indicators available, and the question is, how to deal with the plenty information to end up with one forecast to be published. One possibility would be to test various combinations of indicators to find one set of regressors which has shown a good fit in the past. However, a good fit in the past does not guarantee accurate forecasts, and furthermore, all information contained in indicators omitted will be neglected. Therefore, it is common among forecasters to use systems of bridge equations, which means estimating many different equations, each using a different subset of indicators and different specifications and combining the forecasts of these many equations in one or another way (e.g. Kitchen and Monaco, 2003, Diron 2008, Carstensen et al. 2009, Drechsel and Scheufele 2012, Döhrn et al. 2011: 65-67).

All these models have one problem in common. Whereas GDP is available quarterly, most of the indicators are published monthly, and therefore have to be aggregated to quarterly values in the first place. Since many indicators are released with lags, however, not all the data for the months that make up the present (and even previous) quarter are known. Furthermore, the number of monthly data already known may differ between indicators, generating a ragged edge of the data set. The question now arising is how to deal with missing values in the data set. There are various options (Döhrn 2014b: 103-104). The solution mostly chosen in a bridge equation context is to estimate missing values by using a univariate autoregressive model. The forecast horizon then quite often is extended to get not only a full set of monthly indicators for the current quarter but also for the quarter to come.[12]

These short term extensions of the indicator series form the starting point of our approach. Instead of using only univariate autoregressive processes, for this purpose we make use of weather information. The underlying conjecture is, if it is already known at the time when making a forecast that the winter is extraordinary mild or cold, the use of this information may improve the accuracy of the short term extension

[12] Since National Accounts as well as many indicators are published with some delay, bridge equation models are used during the first 50 days of a quarter to get an estimate of GDP in the previous and the current quarter.

relative to a univariate autoregressive model and subsequently improve the accuracy of GDP forecasts.

In what follows we use the following approach to extend indicator series over the short term:

$$I_t = f(I_{t-1}, I_{t-2}, \ldots, W_t, W_{t-1}, W_{t-2}, \ldots). \quad (2)$$

W is one of the weather variables described above. It is included into the equation coincidently as well as lagged to take into account that extreme weather situations may also influence the indicators in the months to follow.[13]

We will demonstrate our approach here using the short term extension of the production index of the construction sector, which is a rewarding example since construction is one of the economic activities which is strongly influenced by weather. Since the construction index is non-stationary, we estimate the month-over-month growth rate of the index. The estimation period covers the years 1991-2013. As a reference forecast, we choose an ARMA(1,1) model. The AR-term as well as the MA term in this model are highly significant, but the adjusted R^2 is only 0.182 (table 1). The three weather variables are significant up to two lags and they increase the fit of the model impressively. Chart 2 shows the one month ahead out of sample forecasts for the first half of 2014 and compares them to the observed changes in construction production. It becomes evident that in general the equations including the weather variable provide better forecasts than the ARMA process. However there are differences between the weather variables. Apparently, in this special case the ifo indicator generates some undershooting in February after the atypically mild January and again a backlash in March.

However, in these forecasts it is assumed that the weather variables are known over the forecast horizon, which in practice, of course, is not the case. The construction production index for December 2013, which is the last observation in our sample, was published in early February 2014. At this point of time the weather variables were only known for

[13] For each indicator, the lag structure is optimized using the Schwarz Information Criterion.

January. Thus, to extend the series of construction production over the months of the first half of 2014, a weather forecast is needed for the residual five months, February to June. The easiest way is to set the weather variables to 0 for all months. Since the variables are defined as deviations from the long term monthly averages, this would reflect the assumption of usual weather conditions during all five months, February to June. In this setup, the outcome is less convincing, see Chart 3. Again, we get a rather good estimate of the change of production in January. But for the following months the forecast is even less accurate then the ARMA model, and towards the end of the forecast horizon, the forecasts converge towards the ARMA forecasts.

4. Which indicators show weather effects?

In the previous section, production in the construction sector has served as an example of an economic indicator to be influenced by the weather. While construction is the most obvious case, it can be expected that also other economic indicators show weather effects. In some cases a strong winter may enhance production, e.g. in the energy sector, in other cases it will hinder it for technical reasons or because of delivery problems during icy winters.

Subsequently we analyze weather effects on 42 among the 49 economic indicators that enter the RWI short term forecasting model.[14] We start with a simple autoregressive approach. In a next step we analyze whether the fit of the autoregressive regressions can be improved by including the weather variables as additional regressors in these equations.

Given the large number of indicators and regressions, the results of this exercise will be presented here in a non-technical way.[15]

[14] The remaining 7 variables that enter the model are foreign and global economic indicators. They have been excluded from this analysis because it seems implausible that they are influenced by the weather situation in Germany.

[15] The sample of the estimates is 1995 to 2003. If variables are stationary – like most survey based indicators – the left hand variables in the regressions

- Among the diverse survey based *business climate indicators* we find a significant influence of all three weather indicators on business expectations in the construction sector. This is not surprising given construction production is significantly affected by weather. The signs of the parameters show that expectations tend to be more positive during cold winters, which suggests that companies see backlog demand for construction after cold winters.
- Moreover, we find a significant and positive impact of cold winters on the change of the *unemployment rate*. However, we only find a small negative effect of weather with lag 2 which suggest that the catch up of employment after cold winters and the dampening of the increase after mild ones, respectively, is not clear-cut.
- We also find a weather effect in the change of *production* in a number of sectors. A negative coefficient of coincident weather and a positive one of lagged weather can be found in the mining and quarrying sector and in in the production of consumer goods as a whole. This effect is also measurable with regards to total industrial production. However, all these sectors have in common that short term shifts in production can only be insufficiently described by an autoregressive process and that even after including the weather variables the explanatory power of the equations is small.
- A positive effect of coincident weather is detected for the change of the production of *electricity, gas and water*. Here, lagged weather variables are significant, too, and they have negative signs, suggesting that after a weather-induced change of production some normalization will take place in the following months.
- Finally, a weather effect can be found in the change of car registrations. We find a positive effect of the lagged weather variables, which suggests that car sales do not pick up until winter is over.

In almost all cases, the frost days and the temperature deficit variable perform better than the survey based ifo indicator. That may also be owed to the fact that the indicators based on the reporting of the National Meteorological Service contain information for an entire

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are levels. In case they are non-stationary variables, the dependent variable are month over month changes. The results are available upon request.

month whereas the ifo indicator reflects subjective assessments of the respondents collected in the first half of a month.

5. Weather variables in the RWI short term forecasting model

As outlined above, the RWI short term forecasting model is based on a system of bridge equations. It includes 49 indicators in differently specified equations and combinations to generate a large number of forecasts of the quarterly growth rate of GDP in the current and in the next quarter. The results of the model are displayed in form of a distribution of the individual forecasts from which a (weighted) mean is derived. The model offers various options to generate its results. After setting up the system of individual bridge equations, there are different ways to select which of these equations will be used for the averaging of forecasts. Secondly, the arithmetic mean, the mode, or the median can be used to determine a simple mean forecast. Instead, we will use the trimmed arithmetic mean. Trimming means that all equations are ordered according to their past out-of-sample forecast accuracy and that forecasts with an inferior accuracy will be excluded.[16] Here, we will use a trimming factor of 75%; i.e. we cut off the worst performing 75% of the equations or, in other words, base our forecast on the 25% top performing equations.

Before conducting the individual forecasts of a specific GDP growth rate y_t, we determine a rolling window of 24 quarters between t-24 and t-1 to estimate the bridge equations in-sample. In sum, there are 40 GDP growth rates to be forecast. The first forecasts refer to GDP in 2005Q1 and are based on the estimation period 1999Q1-2004Q4, while the last forecasts refer to GDP in 2014Q4 and are based on the estimation period 2008Q4-2014Q3.For each quarter t, we produce six forecasts of Y_t in six subsequent months. The first three forecasts are conducted in the months after Y_{t-2} has been released (months 1-3 in tables 2 and 3). Then, Y_{t-1} will be released and another three forecasts are conducted in the months before Y_t is released (months 4-6 in tables 2 and 3). Over this period the forecasts become increasingly accurate as the short term

[16] The trimming procedure is conducted each time anew before a forecast is made to account for the most recent past of equations' forecast accuracy.

extension of indicators will be substituted increasingly by observed values. To forecast Y_{t+1} and Y_{t+2} in three successive months, we determine a rolling window of 24 quarters between t-24 and t-1 to estimate the bridge equations in-sample. In sum, there are 39 GDP growth rates to be forecast one-step and two-steps ahead. The first forecasts refer to GDP in 2005Q1 and in 2005Q2 and are based on the estimation period 1999Q1-2004Q4, while the last forecasts refer to GDP in 2014Q3 and 2014Q4 and are based on the estimation period 2008Q3-2014Q2. Between 2005 and 2014 the Mean Squared Error (MSE) of the forecasts reduces from 1.018 to 0.636 as we proceed from month 1 to month 6, when no weather variables are included (table 2).[17] The forecast errors are quite large, but they are strongly influenced by large errors during the Great Recession. Excluding the latter from the sample generates significantly lower MSEs (table 3).

Including the weather variables into the short term extension of indicators reduces MSEs in almost all cases considered. However, the advances in terms of a reduction of the MSE are rather small. Not surprisingly, models which use real weather data generate more accurate forecasts in most cases than those, which use forecasted weather variables. Comparing the three weather variables, the ifo survey performs best in most cases. But also here, the differences are small.

In Table 4 the forecasts of the second quarter are evaluated, which is particularly difficult to forecast as it is demonstrated by the MSE above average. In most cases the inclusion of weather variables reduces forecast errors, too. However, advances are rather small again though somewhat more pronounced compared to the average of all quarters.

At the end of the day the question arises why the benefit from including weather information is so small. One reason is that only a small number of indicators show a weather effect and if some of them perform poorly as indicators of GDP, they are even excluded in the trimming process.

[17] To get results that are not spoiled by data revisions, we conduct a quasi-real time analysis. We generate the various harvests of the model based on the latest released data, but only use the sample that was available in the month to which we assign the forecast.

Another reason is that, even if indicators are well-performing indicators of GDP and even if they show a significant weather effect, in most cases the accuracy of the short term extension remains nevertheless poor after including the weather variables. Such is the case e.g., with production in the manufacturing sector.

6. Conclusions

Weather undoubtedly may have a strong influence on economic activity, even in the short run. Seasonal adjustment does not take into account for such effects because weather variables play no role in the model used to conduct these adjustments. In our explorative study we try to identify ways how weather aspects can be incorporated in short term forecasts of German GDP to improve the accuracy of these forecasts. We conduct this analysis in the context of bridge equation models, introducing weather variables at the stage of the short term extension of indicator series into these models.

We propose three different weather variables which can be determined easily. All of them show a significant influence on at least some economic indicators, but to a different degree. In particular the survey based variable from the ifo institute seems to add information not included in purely temperature based weather variables. While the number of indicators influenced by weather is rather small, the weather effect is significant in some economic sectors. This is particularly true for the construction sector. The forecast accuracy of more complex models, such as the RWI short term forecasting model focusing on *total* economic production, can also be improved by including weather variables, but advances are rather small and far from being statistically significant. Nevertheless, our results provide a valuable first step on how to account for effects not covered by seasonal adjustment in economic forecasting in a systematic way.

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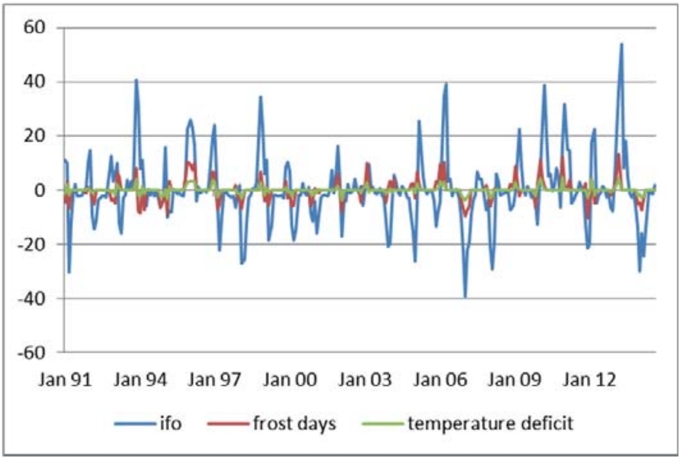
Chart 1

Weather variables

1991-2014



Authors' calculations based on data from Deutscher Wetterdienst and from ifo institute.

Table 1

Time series models of production in the construction sector

Sample Jan. 1991 to Dec. 2013, month-over-month change

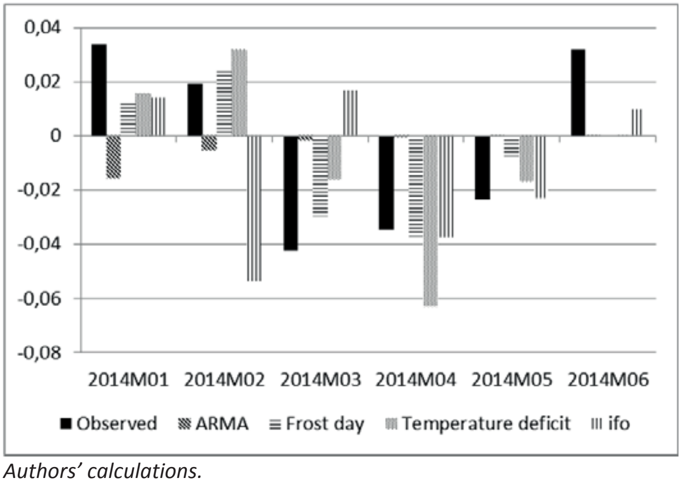
Weather variable	C	AR (1)	MA (1)	W_t	W_{t-1}	W_{t-2}	R^2 adj.
None	-0.0003	0.323	-0.790				0.182
	0.3	3.5	-14.0				
ifo	-0.0003	0.210	-0.749	-0.002	0.003	-0.001	0.362
	0.3	2.4	12.5	6.2	6.9	2.7	
Frost days	-0.0001	0.324	-0.752	-0.008	0.006	0.002	0.458
	0.1	3.3	10.9	11.0	6.7	3.3	
Temperature deficit	0.0001	0.276	-0.718	-0.025	0.019	0.008	0.541
	0.1	2.6	9.5	13.3	8.1	4.4	

Authors' calculations. Below the coefficients: t-values

Chart 2

Out of Sample forecast of production in the construction sector based on observed weather variables

Month-over-month changes of seasonal adjusted data

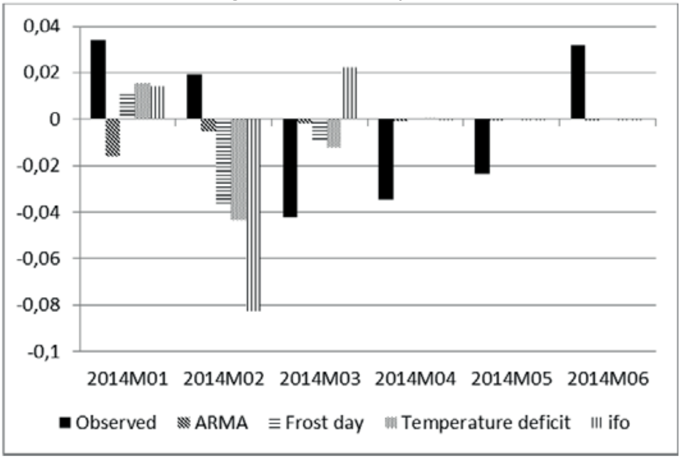


Authors' calculations.

Chart 3

Out of Sample forecast of production in the construction sector based on forecasted weather variables after January 2014

Month over month changes of seasonal adjusted data



Authors' calculations

Table 2

Forecast accuracy of the RWI short term forecast model[1]

2005-2014; Mean Squared Forecast Error

	Without weather variable	Frost days	temperature deficit	ifo survey
		True weather data		
Month 1	1.088	1.083	1.085	1.069
Month 2	1.002	0.997	0.994	1.002
Month 3	0.907	0.891	0.902	0.881
Month 4	0.893	0.883	0.878	0.875
Month 5	0.742	0.734	0.742	0.732
Month 6	0.613	0.606	0.606	0.609
		Naïve weather forecast[2]		
Month 1	1.088	1.072	1.088	1.066
Month 2	1.002	1.002	0.999	1.001
Month 3	0.907	0.891	0.882	0.887
Month 4	0.893	0.886	0.879	0.876

Authors' computations. – [1]Trimmed arithmetic Mean; trimming factor 75%. – [2]Results for months 5 and 6 are the same as in the section above.

Table 3

Forecast accuracy of the RWI short term forecast model[1]

2005-2014 without Great Recession[2]; Mean Squared Forecast Error

	Without weather variable	Frost days	temperature deficit	ifo survey
		True weather data		
Month 1	0.467	0.457	0.454	0.457
Month 2	0.417	0.414	0.412	0.415
Month 3	0.351	0.344	0.356	0.333
Month 4	0.282	0.276	0.278	0.269
Month 5	0.258	0.249	0.251	0.248
Month 6	0.236	0.232	0.232	0.234
		Naïve weather forecast[3]		
Month 1	0.467	0.453	0.467	0.452
Month 2	0.417	0.419	0.416	0.418
Month 3	0.351	0.344	0.339	0.334
Month 4	0.282	0.275	0.272	0.273

Authors' computations. – [1]Trimmed arithmetic Mean; trimming factor 75%. – [2] 2008Q4, 2009Q1 and 2009Q2. - [3] Results for months 5 and 6 are the same as in the section above.

Table 4

Accuracy of the forecast of Q2 from the RWI short term forecast model[1]

2005-2014 without Great Recession Mean Squared Forecast Error

	Without weather variable	Frost days	temperature deficit	ifo survey
	True weather data			
Month 1	0.723	0.712	0.703	0.703
Month 2	0.739	0.728	0.721	0.728
Month 3	0.618	0.623	0.621	0.593
Month 4	0.623	0.603	0.612	0.593
Month 5	0.550	0.547	0.551	0.545
Month 6	0.505	0.502	0.502	0.499
	Naïve weather forecast[2]			
Month 1	0.723	0.721	0.723	0.706
Month 2	0.739	0.749	0.738	0.744
Month 3	0.618	0.623	0.611	0.602
Month 4	0.623	0.602	0.593	0.590

Authors' computations. – [1]Trimmed arithmetic Mean; trimming factor 75%. –[2]Results for months 5 and 6 are the same as in the section above.

Table 5

Indicators included in the RWI short term forecasting model

New orders, volume, domestic; Electrical & opt. equipment; 2010=100, sa
New orders, volume, domestic; Motor vehicles; 2010=100, sa
New orders, volume, domestic; Durable consumer goods; 2010=100, sa
New orders, volume, domestic; Consumer goods; 2010=100, sa
New orders, volume, domestic; Chemicals; 2010=100, sa
New orders, volume, foreign; Consumer goods; 2010=100, sa
New orders, volume, foreign; Durable consumer goods; 2010=100, sa
New orders, volume, total; Motor vehicles; 2010=100, sa
New orders, volume, total; Buildings & civil engineering; 2010=100, sa
New orders, volume, total; Buildings; 2010=100, sa
New orders, volume, total; Residential buildings; 2010=100, sa
New orders, volume, total; Civil engineering; 2010=100, sa
New orders, volume, total; Durable consumer goods; 2010=100, sa
New orders, volume, total; Consumer goods; 2010=100, sa
Production; Buildings & civil engineering; 2010=100, sa
Production; Mining & quarrying; 2010=100, sa
Production; Durable consumer goods; 2010=100, sa
Production; Electricity, gas & water; 2010=100, sa
Production; Consumer goods; 2010=100, sa
Production; Total industry; 2010=100, sa
Registrations; New passenger cars; 1000
Retail sales; Clothing, footwear & leather goods; Value, 2010=100, sa
Exports; Passenger cars; 1000
Merchandise exports, fob; Bn Euro, sa
Unemployment rate; Based on registrations; % of labor force
Money supply M1; Level, bn Euro
Money supply M2; Level, bn Euro
Consumer price; 2010=100, sa
Wholesale price; 2010=100
Commodity price (HWWI); Raw materials, total; US$ based, 2010=100; Monthly av.
Commodity price (HWWI); Raw materials, excl. energy; US$ based, 2010=100; Monthly av.

Table 5 (continued)

FAZ share price index; 1958.12=100
VDAX share volatility index; % p.a.
Citigroup money market performance index; Local currency, 1997.12.31=100
Exchange rate; ¥/Euro; Monthly average
Exchange rate; Trade-weighted, real, partner currencies/US$; 2010=100
Business Climate; Wholesale trade incl. trade with cars; 2005=100, sa
Business Expectations; Construction sector; next 6 months; 2005=100, sa
Business Expectations; Retail trade incl. trade with cars; next 6 months; 2005=100, sa
Business Expect.; Wholesale trade incl. trade with cars; next 6 months; 2005=100, sa
Business Expectations; Industry; 2005=100, sa
Leading indicator (ZEW Indicator of Economic Sentiment); 0=neutral
Business confidence; Services; Balance, %, sa;
Production; Manufacturing; 2007=100, sa; US economy
Production; Consumer goods; 2007=100, sa; US economy
Private consumption; At chained 2009 prices, bn US$, sa; US economy